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Observed Temperature Effects on Hourly Residential Electric Load Reduction in Response to an Experimental Critical Peak Pricing Tariff

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Abstract

The goal of this investigation was to characterize the manual and automated response of residential customers to high-price "critical" events dispatched under critical peak pricing tariffs tested in the 2003-2004 California Statewide Pricing Pilot. The 15-month experimental tariff gave customers a discounted two-price time-of-use rate on 430 days in exchange for 27 critical days, during which the peak period price (2 p.m. to 7 p.m.) was increased to about three times the normal time-of-use peak price. We calculated response by five-degree temperature bins as the difference between peak usage on normal and critical weekdays. Results indicated that manual response to critical periods reached -0.23 kW per home (-13%) in hot weather (95-104.9°F), -0.03 kW per home (-4%) in mild weather (60-94.9°F), and -0.07 kW per home (-9%) during cold weather (50-59.9°F). Separately, we analyzed response enhanced by programmable communicating thermostats in high-use homes with air-conditioning. Between 90°F and 94.9°F, the response of this group reached -0.56 kW per home (-25%) for five-hour critical periods and -0.89 kW/home (-41%) for two-hour critical periods.

Introduction

High wholesale prices associated with short-term spikes in electric demand can significantly increase average utility costs and customer rates. Distribution congestion and related reliability issues can also affect the relative cost of peak service. One way to encourage load reductions during such critical peak periods is through dynamic pricing, which enables changes to retail electricity rates on an hourly or daily basis to better reflect real-time wholesale costs and reliability needs. Dynamic pricing has long been considered an economically efficient approach to reducing short-term demand and price spikes [1-3].

In May of 2003, the California Public Utilities Commission approved funding for the Statewide Pricing Pilot (SPP). The main goal of the pilot and the accompanying impact evaluation was to develop an econometric model for predicting demand response[1] under alternative pricing plans [4, 5]. The goal of the analysis presented in this paper is to augment the results of the SPP impact evaluation data by providing evidence of how residential demand response changes with temperature.

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[1] Throughout this paper, we use the term "response" to indicate the difference between the actual amount of electricity used and the baseline amount that would have been used in the absence of the critical event stimulus: i.e. response = actual - baseline. Thus, a more negative response indicates a higher load drop.

Maximum peak loads in California occur during hot weather, when air-conditioning demands are high. Figure 1 shows the relationship between average statewide temperature and loads in the California Independent System Operator (ISO) control area for 2004. In this year, the maximum daily peak load was 45.6 GW on a day when the average statewide peak temperature was 90°F [6]. These maximum peaks are projected to increase by 1.7% per year through 2010, driving the need for about one gigawatt (GW) of new generation capacity annually [7]. One way to meet maximum peaks is to build peaking generators, which can cost over $500 per megawatt-hour (MWh) [8]. Along with the costs of sizing transmission and distribution systems to meet the highest possible peak loads, the fully-allocated cost of serving peak loads is many times higher than the cost of serving the average load. To minimize these peak expenditures, California is working towards a goal of meeting 5% of peak load with price-induced demand response by 2007 [9].

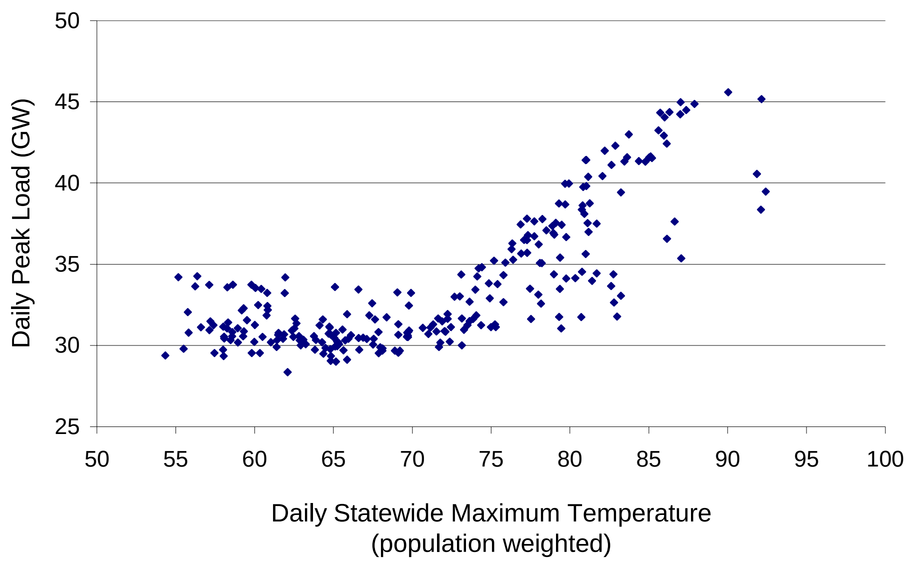

Figure 1. Daily peak loads as a function of temperature, California ISO weekdays 2004 [6]

Most electricity rates in use today are not dynamic, but are instead what we call "static," meaning that retail prices have been decided for all hours, and can only be changed by changing the electricity tariffs - a process that can take months or years. Dynamic rates, in contrast, afford utilities the option to change or “dispatch” prices on short notice in response to temporary system or wholesale pricing conditions. The five graphs showing hourly prices in Figure 2 illustrate the difference between dynamic and static rates and some of the possible variations of each. The fully predictable static rates include flat and time-of-use (TOU) rates. We consider all rates without diurnal time variation to be flat – this includes tiered rates such as those common in California. TOU rates, in contrast, offer reduced off-peak prices in exchange for increased peak prices, with the intent of reducing daily peak loads. Dynamic rates differ in that they allow dispatchable prices. Common dynamic rate types include critical peak pricing (CPP) and real-time pricing (RTP). Under a CPP rate, prices are reduced on normal days in exchange for high peak prices on “critical” days, which are typically triggered according to supply, demand, temperature, wholesale prices or some combination of these. RTP rates, in contrast, are updated every day on an hourly or sub-hourly basis, to closely mirror wholesale prices. Both CPP and RTP rates require that customers be given advance notice of upcoming price changes, and both can be coupled with technologies that allow automatic modification of end-use loads according to customer or utility preferences.

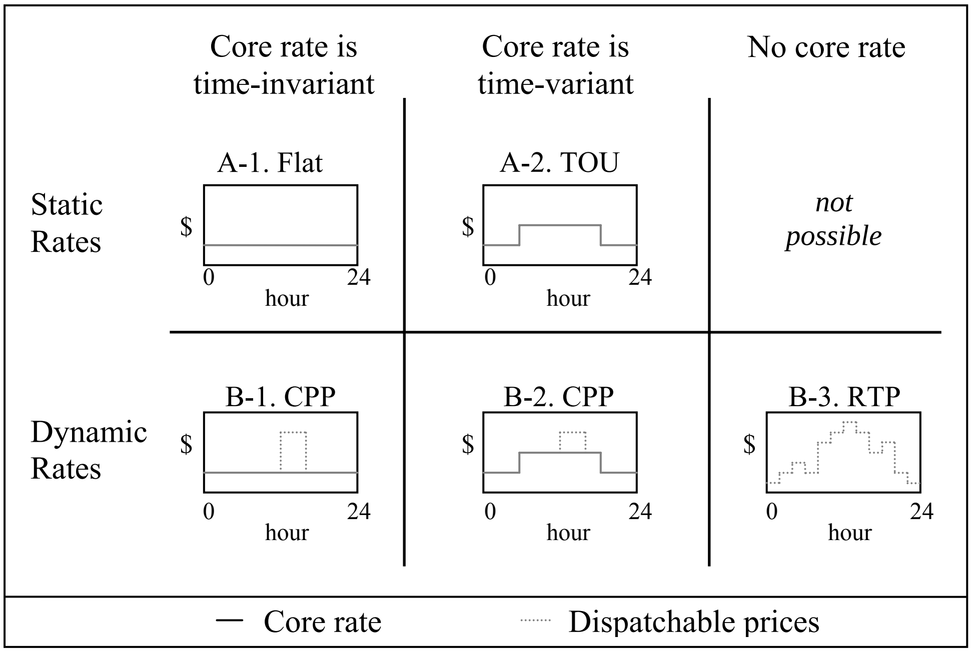

Figure 2. Rate types showing static and dynamic components

Several studies of residential response to CPP rates have been conducted. Unfortunately, inconsistencies in pricing, experimental design, analysis and reporting complicate presentation and comparison of results. Calculation of price elasticity values is often used to normalize price differences, but cannot address other rate discrepancies, such as core rate type or the number, duration and timing of critical peak events. While the prevalence of econometric evaluation implies that many consider the rate to be the most important variable, other variables that can affect response include temperature, the existence and characteristics of control technologies, the existence and characteristics of event notification, participant education and information provided before and during the experiment, and the demographics of the sample, to name just a few. These problems, combined with inconsistent analysis techniques and insufficient reporting make direct comparison between studies or extrapolation to new programs nearly impossible.

The residential dynamic rate pilots that have been conducted in the U.S. can be divided into two categories: those with and those without automated control technologies. Studies of the former type report that participants on CPP rates with control technologies use 30-40% less electricity during critical events than do control groups on flat rates [10-12]. Until the California SPP, studies of how customers respond to dynamic rates in the absence of control technologies were almost non-existent. A recent analysis of real-time pricing without communicating technology at a small energy cooperative in Chicago reports an average load reduction of about 10% in the first two hours after a high-price notification, but near zero reduction when averaged over a five-hour period [13]. Despite the respectable response rates reported by these pilot evaluations, full-scale programs are not widespread. This is partly because of the high costs of the metering and response technologies used in the pilots. Also responsible is hesitation on the part of policy makers and utilities to initiate such a politically controversial change without certainty of success in their own service territories. Such certainty can be attained only at the expense of considerable time and money invested in additional pilot testing.

Two factors have caused many states and utilities to seriously consider dynamic pricing for the residential sector. First, market problems encountered in California and elsewhere during the electricity crisis of 2000 and 2001 lent support to arguments in favor of linking short-term retail and wholesale costs. Second, technology advances contributed to declining costs for the advanced metering infrastructure that dynamic rates require. Together, these factors prompted an unprecedented interest in advanced metering and dynamic pricing across the U.S. In California, state agencies and utilities designed and implemented the Statewide Pricing Pilot to test the effectiveness of CPP tariffs with interval meters and customer notification, both with and without the use of response technologies [4]. The *Impact Evaluation of the California Statewide Pricing Pilot* (SPP Impact Evaluation) calculated price elasticity values based on the price and load data, and then used these values to model corresponding load impacts [5].

The analysis described in this paper augments the SPP Impact Evaluation by providing a detailed breakout of how response changes with temperature. Since system demand is closely related to temperature, this approach provides insights on the question of whether load reductions are greatest when they are most needed, typically on very hot days when system demands are high. The results presented here can also be extrapolated to estimate expected response for any local or regional temperature distribution.

Data Collection and Description

Data analyzed for this paper were collected in the California SPP, a complex experiment involving about 2500 residential and small commercial customers. The discussion presented here will focus on describing just the subset of participants to be used in this analysis: the 656 residential SPP participants on a CPP rate without control technology and the 122 residential SPP participants on a CPP rate with programmable communicating thermostats (PCTs). Following is a brief description of the experimental design for the California SPP. For more detailed information, the reader is directed to consult the SPP Impact Evaluation [5].

Sampling for the Statewide Pricing Pilot

As described above, this analysis includes data from two residential CPP treatment groups in the SPP. The group without response technologies we refer to as the “manual” group, while the group with programmable communicating thermostats we call the “PCT” group. These two sample groups are taken from two different populations, so their results are not directly comparable.

To take advantage of existing hardware, the 122 PCT group participants included in this study were solicited from a large thermostat load-control program in the San Diego Gas and Electric service territory. All participants of the original load-control program were high-use (>600 kWh/month), single-family homes with central air-conditioning [14]. The PCTs allowed automatic control of air-conditioning units when the critical event signal was received.

Sampling for the manual group was stratified by building type and climate zone with the intent of producing a group that was representative of the California population. The sample design for the manual group made use of 12 strata as shown in Table 1. We roughly describe the climate zones as Coast, Foothills, Valley and Desert, where the Coast includes Arcata, San Francisco, Salinas and San Luis Obispo; the Foothills include Santa Rosa, San Jose, Oxnard, Long Beach and western San Diego; the Valley includes Chico, Stockton, Santa Clarita, Riverside and eastern San Diego; and the Desert includes Redding, Fresno, Bakersfield and Palm Springs. The statewide weights in Column D indicate the percentage of the California population in each stratum. Later, we use these values to weight within-stratum load impact estimates to be representative of the state. The values in Column E indicate the number of SPP participants in each stratum.

Table 1. Sample design for the manual CPP group

A. Stratum	B. SPP climate zone - description	C. Dwelling/usage type	D. Statewide population weight	E. Sample size
1	1- Coast	Apartment	5%	24
2	1- Coast	Single-family, High usage	2%	21
3	1- Coast	Single-family, Low usage	5%	16
4	2 - Foothills	Apartment	15%	64
5	2 - Foothills	Single-family, High usage	10%	101
6	2 - Foothills	Single-family, Low usage	22%	62
7	3 - Valley	Apartment	6%	47
8	3 - Valley	Single-family, High usage	8%	101
9	3 - Valley	Single-family, Low usage	15%	81
10	4 - Desert	Apartment	2%	28
11	4 - Desert	Single-family, High usage	3%	70
12	4 - Desert	Single-family, Low usage	5%	41
			TOTAL	656

Potential participants for the manual group were randomly selected from within each stratum. They were then sent enrollment packages notifying them that they had been selected to “participate in an important statewide research project,” promising a total participation incentive payment of $175 over the course of the experiment. Contact with chosen customers was repeatedly attempted until (1) they agreed to participate, (2) they declined to participate, or (3) two weeks had passed without contact. As customers declined or were deemed unreachable, replacement customers within the stratum were sent enrollment packages. Ultimately, about 20% of customers accepted the invitation to participate, 15% declined to participate, and the remaining 65% were unreachable or otherwise excluded. Surveys and subsequent analysis indicated that the final sample was a representative cross-section of California residents by appliance holdings, income, education, and 16 other measured variables [15].

Materials and Methods for the Statewide Pricing Pilot

All SPP participants were supplied with new electricity meters that collected usage values at 15-minute intervals. Installation of most meters was conducted between April and June of 2003. Load data collection began for each participant as the meter was installed, and the new time-varying rates were put into effect on July 1, 2003. Load data collected before treatment rates went into effect was collected as "pretreatment data." For participants who enrolled after July 1, 2003, pre-treatment data were collected for about a month before their new rates were initiated.

The experimental CPP tariffs tested in the California SPP correspond to rate type B-2 in Figure 2, consisting of a two-price TOU rate on normal days and a critical peak price on critical days. Twelve times each summer (May through October) and three times each winter (November through April), the critical price was charged over the five-hour peak, from 2 p.m. to 7 p.m. on weekdays. Numerous rates were applied across the three utilities and multiple climate zones. Roughly speaking, average prices were about 10 cents/kWh during off-peak hours, 20 cents/kWh during peak hours, and 60 cents/kWh during critical peak hours (see Figure 3). For comparison, the average electricity price for the average non-participating California customer was about 13 cents/kWh.[2]

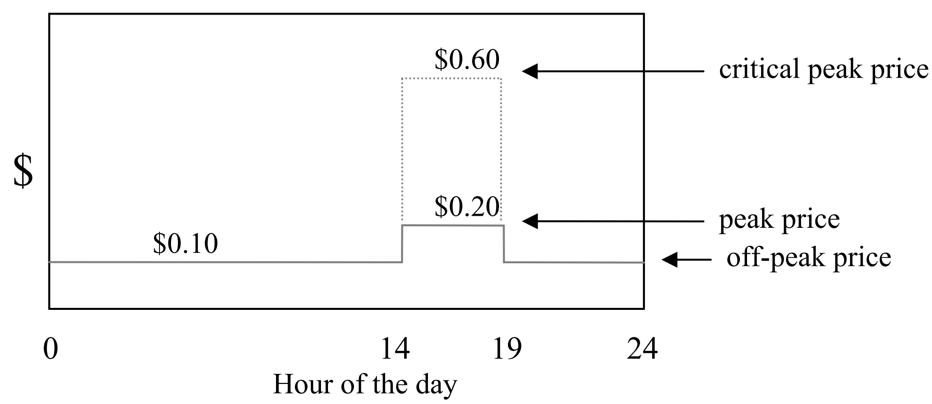

Figure 3. Average prices for the residential CPP tariffs used in the SPP. (Actual prices varied by location, monthly usage, season and treatment group.)

Between July 1, 2003 and September 30, 2004, a total of 27 critical events were called: 7 occurred on Mondays, 6 on Tuesdays, 5 on Wednesdays, 5 on Thursdays, and 4 on Fridays. CPP customers without PCTs were notified by telephone of an impending critical event by 4 p.m. on the day before the event took place. CPP customers with PCTs were notified four hours before the event was to take place, and their PCTs were signaled at the onset of the critical period.[3]

Analysis and Results

As noted previously, an important aspect of this analysis is that we compare each participant's consumption on critical weekdays to their consumption on normal weekdays. As a result, the impacts presented in this paper are the *incremental* impacts of CPP events: those impacts *beyond* the impact of the core TOU pricing compared to the flat rate. We chose this method because:

1. response to time-of-use rates has been well studied
2. after initial adjustment to the new tariff, customers will only "respond" to the dynamic portion of the rate; i.e., response to the TOU component happens within a

[2] To ensure comparability with the control rate, the experimental rates designed for the SPP combined the default inclining block rate structure with the new time-varying and dispatchable components.

[3] For technical reasons, SPP thermostat group participants were not allowed to choose the default temperature change during events, but were allowed to change the temperature setting at any time.

brief window after rates are initiated, while response to the CPP component of the rate occurs at each critical event[4], and

3. our approach allows us to avoid the use of pretreatment data to adjust for self-selection bias.[5]

Because the manual and PCT sample groups and analysis differ substantially, we divide the remainder of this section into two parts. The first part describes the data analysis and results for the manual group. The second part describes the data analysis and results for the PCT group.

Manual Group Response

To ensure reasonable comparability between load on normal and critical days, we disaggregate the load data into five-degree temperature bins as shown in Table 2. Temperature ranges are defined using maximum temperatures recorded during peak hours at each of 58 weather stations geographically assigned to participants. The values in Column B indicate that the mean temperatures for each range were similar for normal and critical days. In general, negative values in the colder temperature ranges, and positive values in the hotter temperature ranges will have the effect of underestimating response results. Column C shows the distribution of critical events across the temperature ranges for the SPP. Note that the SPP critical events were determined according to experimental design rather than according to true electrical emergencies. Historically – excluding the anomalous winter of 2000-2001 – electric system emergencies in California occur most often when much of the state is experiencing very high temperatures.

Table 2. Description of temperature range data for manual group

A. Temp Range (°F)	B. Average Temp Difference (°F): Critical – Normal	C. Distribution of SPP Customer-Events	D. Number of Participants Exposed	E. Statewide Population Represented
50 - 54.9	-0.2	4%	242	42%
55 - 59.9	-0.3	4%	340	57%
60 - 64.9	-0.3	3%	211	39%
65 - 69.9	0.4	4%	158	38%
70 - 74.9	0.6	8%	218	53%
75 - 79.9	0.0	13%	318	68%
80 - 84.9	-0.4	12%	386	77%
85 - 89.9	0.5	11%	465	77%
90 - 94.9	-0.1	12%	340	57%
95 - 99.9	0.2	14%	364	42%
100 - 104.9	0.4	13%	287	32%

Column D lists the number of pilot participants exposed to at least one normal and one critical day with maximum peak temperatures in the given temperature range. In Column E, we show the percentage of California customers represented by that number. So, for

[4] Response in the form of additional efficiency investment continues long after initiation of the rate. This paper focuses on real-time short-term response.

[5] There is some debate about how accurately the SPP pretreatment load data reflects uninfluenced pre-experiment load, since customers received information and instructions about how to reduce peak loads prior to the pretreatment period.

example, the 287 participants that experienced both normal and critical days between 100°F and 104.9°F during the pilot represents 32% of the California population. The other 369 participants, representing 68% of California customers, did not experience these high temperatures; thus we cannot say anything about how they would respond under such conditions. Note that the percentages shown in Column E are not simply the quotient of the participants exposed (Column D) and the total number of participants (656) because of the stratum weighting associated with the values in Table 1.

The first step in our analysis is to calculate hourly load data by averaging across the four 15-minute load readings in each hour. For each temperature range, we then calculate mean 24-hour load shapes for both normal and event days as follows:

1. **Calculate mean customer load shapes by averaging across days, within customer.** This step ensures that each participant is counted only once. Participants not having load data for both normal and critical days are excluded.
2. **Calculate mean stratum load shapes by averaging across customers, within stratum.** The result of this step for the manual group is two sets of 12 load shapes per temperature range, one for each stratum.
3. **Calculate mean statewide load shapes by applying population and exposure weightings to each stratum**. Population weights indicate the actual statewide percentage of customers in each stratum, while exposure weights indicate the percentage of participants actually exposed to the temperatures in the range. Together, the weighting scheme provides expected statewide load shapes for those customers exposed to temperatures within the range.

Together, these three steps result in two sets of 24 mean hourly values: one for normal days and one for critical days. The final hourly mean response values are then calculated as the difference between the normal and critical values. Mathematically, our calculation for mean statewide hourly response can be represented as shown in Eq. 1 in Appendix A. Table 3 shows per household peak (Column A) and off-peak (Column B) usage results for the manual response group, including normal usage, critical usage, response estimates and standard errors for the response estimates. Column C shows the change in average daily consumption between normal and critical weekdays.

Table 3. Average manual household (hh) usage and response, by 5°F temperature bins

	A. PEAK HOURS					B. OFF-PEAK HOURS					C. DAILY
Temp *(°F)*	Normal *(kW/hh)*	Critical *(kW/hh)*	Δ_{kW} *(kW/hh)*	SE(Δ_{kW}) *(kW/hh)*	$\Delta_{\%}$ (%)	Normal *(kW/hh)*	Critical *(kW/hh)*	Δ_{kW} *(kW/hh)*	SE(Δ_{kW}) *(kW/hh)*	$\Delta_{\%}$ *(%)*	$\Delta_{\%}$ *(%)*
50-54.9	0.88	0.78	-0.09	0.033	-11%	0.78	0.78	0.00	0.030	0%	-2%
55-59.9	0.80	0.75	-0.05	0.024	-7%	0.74	0.75	0.01	0.025	1%	0%
60-64.9	0.70	0.76	0.05	0.048	8%	0.65	0.70	0.05	0.028	8%	8%
65-69.9	0.58	0.54	-0.04	0.023	-7%	0.56	0.55	-0.01	0.022	-3%	-4%
70-74.9	0.60	0.58	-0.01	0.025	-2%	0.59	0.60	0.01	0.020	1%	1%
75-79.9	0.67	0.63	-0.04	0.015	-6%	0.62	0.63	0.01	0.016	2%	0%
80-84.9	0.75	0.71	-0.04	0.021	-6%	0.64	0.66	0.02	0.017	3%	1%
85-89.9	0.91	0.85	-0.06	0.026	-7%	0.72	0.74	0.02	0.020	3%	0%
90-94.9	1.06	1.02	-0.04	0.030	-4%	0.78	0.82	0.04	0.021	5%	2%
95-99.9	1.57	1.33	-0.24	0.039	-15%	1.06	1.03	-0.03	0.030	-3%	-6%
100-104.9	1.80	1.59	-0.21	0.062	-12%	1.21	1.20	-0.01	0.044	-1%	-4%

Figure 4 shows the average peak period response for each temperature range. For each temperature range, we have also presented from Table 2 the percentage of California homes represented by the response results. The overall trend indicates that response, like load, peaks at the higher temperatures and to a lesser extent at the lower temperatures. Visual examination of Figure 4 indicates similar response across the temperature ranges 50-59.9°F, 60-94.9°F, and 95-104.9°F. Based on this observation, we simplify further graphical representation of results by averaging over the 5°F bins within these cold, mild, and hot temperature ranges. Table 4 provides a consolidated version of Table 3 based on this aggregation.

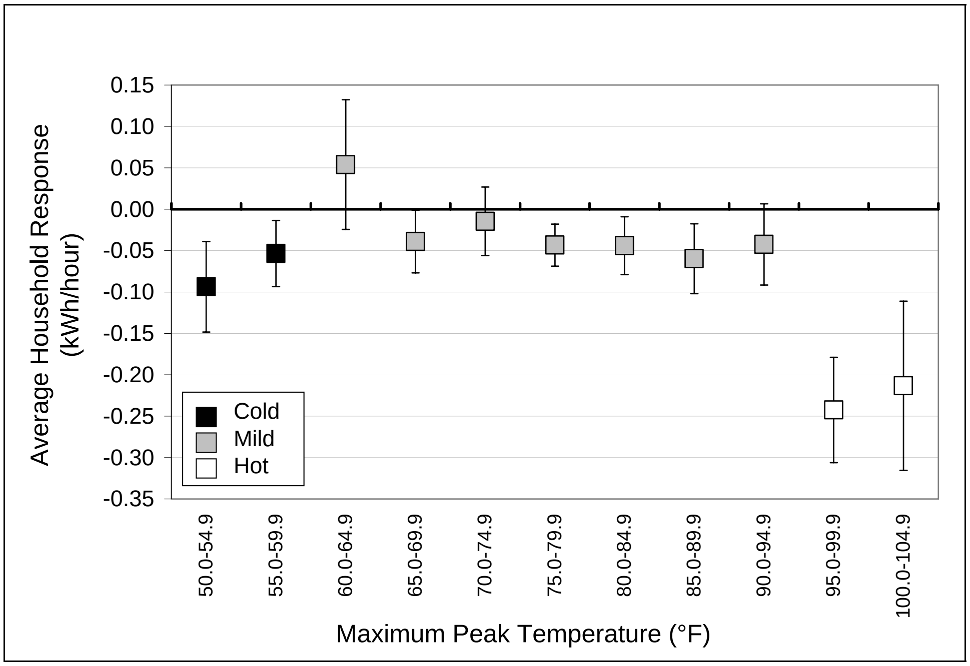

Figure 4. Average customer response as a function of temperature, in kWh/hour

Table 4. Average household (hh) usage on normal and critical days, by temperature range

		A. PEAK HOURS					B. OFF-PEAK HOURS					C. DAILY
Day-type	Temp *(°F)*	Normal *(kW/hh)*	Critical *(kW/hh)*	Δ_{kW} *(kW/hh)*	SE(Δ_{kW}) *(kW/hh)*	$\Delta_{\%}$ (%)	Normal *(kW/hh)*	Critical *(kW/hh)*	Δ_{kW} *(kW/hh)*	SE(Δ_{kW}) *(kW/hh)*	$\Delta_{\%}$ *(%)*	$\Delta_{\%}$ *(%)*
Cold	50-59.9	0.84	0.77	-0.07	0.029	-9%	0.76	0.76	0.01	0.028	1%	0.84
Mild	60-94.9	0.75	0.73	-0.03	0.028	-4%	0.65	0.67	0.02	0.021	3%	0.75
Hot	95-104.9	1.69	1.46	-0.23	0.052	-13%	1.13	1.11	-0.02	0.038	-2%	1.69

Figures 5, 6 and 7 show average hourly household electricity consumption in kilowatts (kW) on normal and critical days for hot, mild and cold temperatures, respectively. Critical event periods are marked by the shaded areas and confidence intervals (α=0.1) are given for each hourly value. N represents the sum of data points across temperature bins; thus a single customer can be counted more than once per graph, because each graph aggregates several temperature bins. In Figure 5 (95-104.9°F), we see significant response averaging -0.23 kW across all five critical hours. Outside the event period, the difference between usage values on normal and critical days is negligible. The difference between the two load shapes in Figure 6 (60-94.9°F) is nearly imperceptible, with a mean response of only -0.03 kW during event hours. In Figure 7 (50-59.9°F), loads appear to increase a considerable amount in the mornings before the critical events, implying some load shifting. Response appears negligible in the first three hours of the event, and increases significantly in the fourth and fifth hours, for a mean response of -0.07 kW per home.

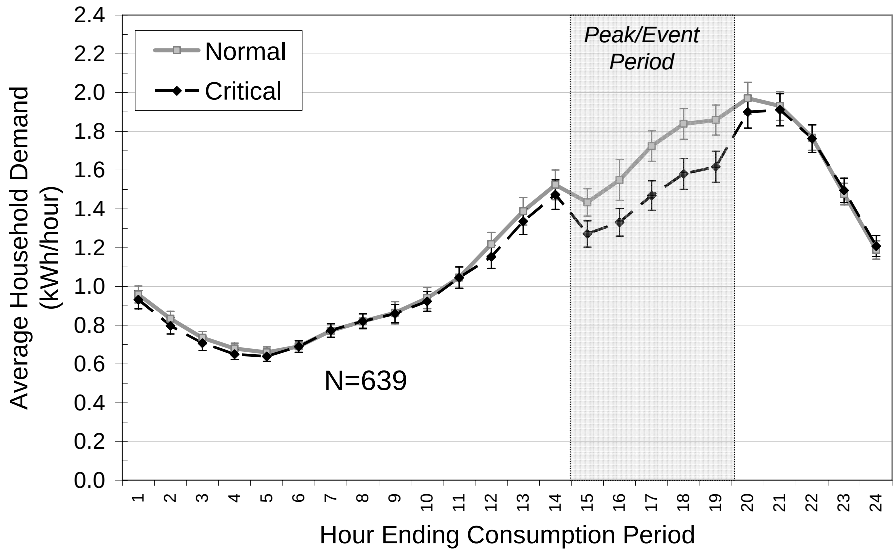

Figure 5. Hourly usage on normal and critical days during hot weather, 95-104.9°F

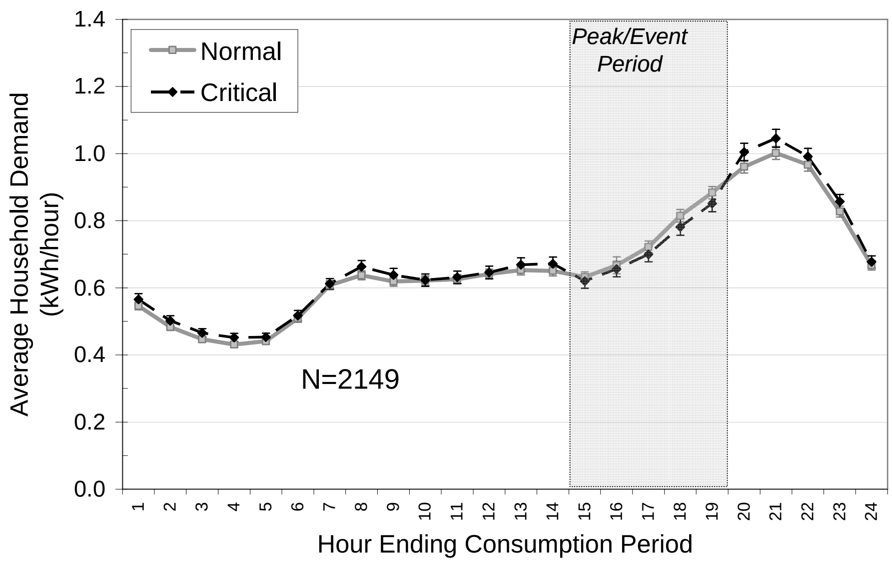

Figure 6. Hourly usage on normal and critical days during mild weather, 60-94.9°F

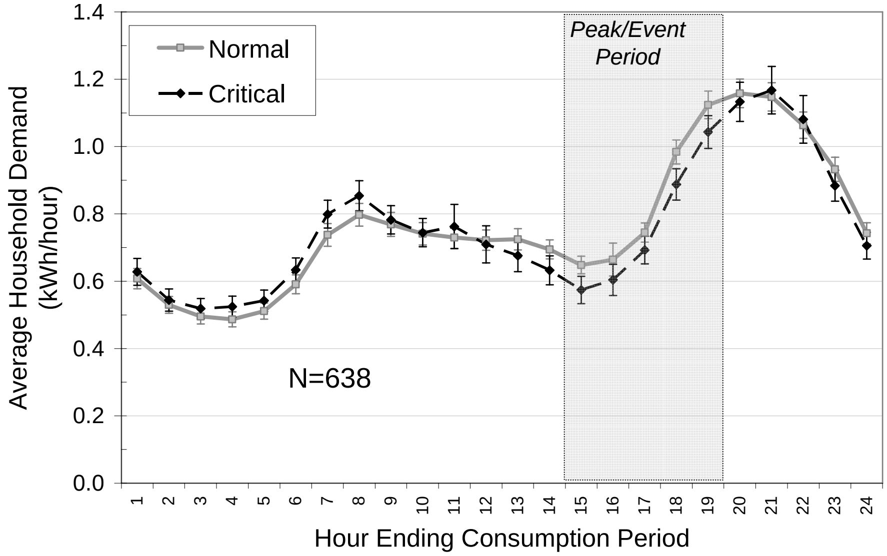

Figure 7. Hourly usage on normal and critical days during cold weather, 50-59.9°F

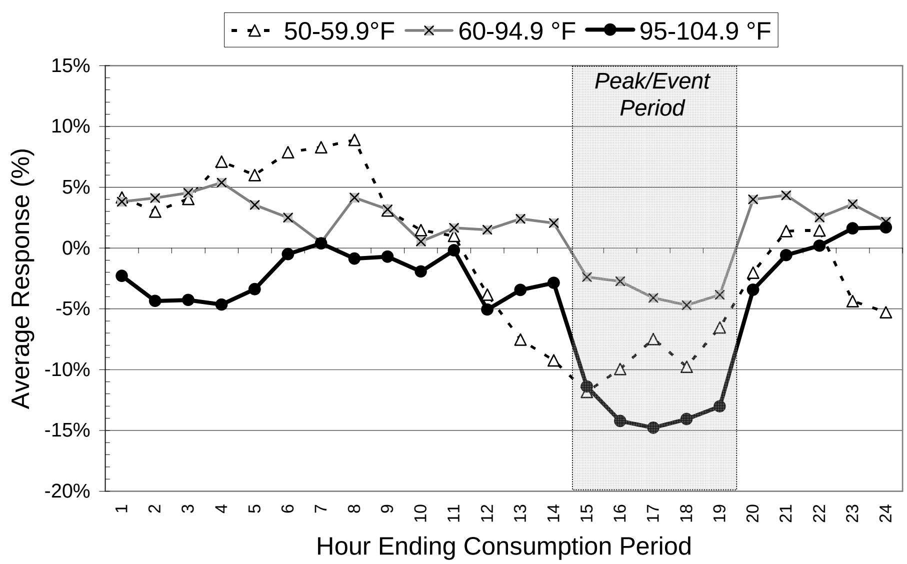

Figure 8. Average hourly load response (%), by temperature

Figure 8 shows hourly response patterns as a percentage of normal-day loads. The greatest response as a fraction of load is obtained on the hot days (95-104.9°F), which average -13% response across the five peak hours. These reductions appear to come mainly as a result of conservation rather than load shifting, as off-peak load increases are minimal and total daily energy use decreases by 5%. On cold days, peak response averages -9% and daily consumption decreases by only 1%, owing to increased loads in the morning hours before the critical event. During mild temperature days, events averaging a -4% response are preceded and followed by higher than typical loads, so that overall daily consumption increases by 1%.

PCT Group Response

The analysis for the PCT group mirrors the analysis described above with the following exceptions.

- Sufficient data existed only for temperature bins from 70 to 94.9
- The PCT group was not stratified; thus the calculation represented by Eq. 1 in Appendix A is simplified by solving for one stratum rather than twelve.
- Some critical events were five hours long while others were two hours long. Separate analyses address these different event lengths.

Table 5 and Table 6 summarize the PCT group characteristics and their average critical peak response by temperature for five- and two-hour events, respectively. In all temperature ranges, five-hour events elicit much lower peak reductions and higher off-peak increases than do two-hour events. This contributes to the result that, overall, energy use on five-hour event days is substantially higher than energy use on normal days, particularly between 75°F and 89.9°F. A similar but less pronounced effect is seen on two-hour event days. Figure 9 shows the average response by temperature range for both CPP event lengths.

Table 5. Average PCT household (hh) usage and response, five-hour critical period

		A. PEAK HOURS					B. OFF-PEAK HOURS					C. DAILY
Temp *(°F)*	N	Normal *(kW/hh)*	Critical *(kW/hh)*	Δ_{kW} *(kW/hh)*	SE(Δ_{kW}) *(kW/hh)*	$\Delta_{\%}$ (%)	Normal *(kW/hh)*	Critical *(kW/hh)*	Δ_{kW} *(kW/hh)*	SE(Δ_{kW}) *(kW/hh)*	$\Delta_{\%}$ *(%)*	$\Delta_{\%}$ *(%)*
70 - 74.9	93	1.06	0.97	-0.09	0.03	-8%	1.01	0.99	-0.01	0.02	-1%	-3%
75 - 79.9	110	1.25	1.25	-0.01	0.03	-1%	1.06	1.19	0.13	0.02	13%	10%
80 - 84.9	118	1.48	1.40	-0.08	0.03	-6%	1.14	1.29	0.14	0.03	13%	8%
85 - 89.9	61	1.68	1.56	-0.12	0.05	-7%	1.22	1.47	0.25	0.04	20%	13%
90 - 94.9	90	2.20	1.64	-0.56	0.07	-25%	1.39	1.49	0.09	0.06	7%	-3%

Table 6. Average PCT household (hh) usage and response, two-hour critical period

		A. PEAK HOURS					B. OFF-PEAK HOURS					C. DAILY
Temp *(°F)*	N	Normal *(kW/hh)*	Critical *(kW/hh)*	Δ_{kW} *(kW/hh)*	SE(Δ_{kW}) *(kW/hh)*	$\Delta_{\%}$ (%)	Normal *(kW/hh)*	Critical *(kW/hh)*	Δ_{kW} *(kW/hh)*	SE(Δ_{kW}) *(kW/hh)*	$\Delta_{\%}$ *(%)*	$\Delta_{\%}$ *(%)*
70 - 74.9	65	0.89	0.77	-0.12	0.07	-14%	0.94	0.92	-0.03	0.10	-3%	-4%
75 - 79.9	175	1.22	1.07	-0.15	0.04	-13%	1.06	1.15	0.09	0.06	8%	6%
80 - 84.9	227	1.45	1.21	-0.24	0.04	-16%	1.18	1.25	0.07	0.06	6%	-2%
85 - 89.9	149	1.70	1.40	-0.30	0.07	-17%	1.28	1.40	0.12	0.09	9%	6%
90 - 94.9	75	2.19	1.29	-0.89	0.13	-41%	1.49	1.31	-0.19	0.14	-13%	-16%

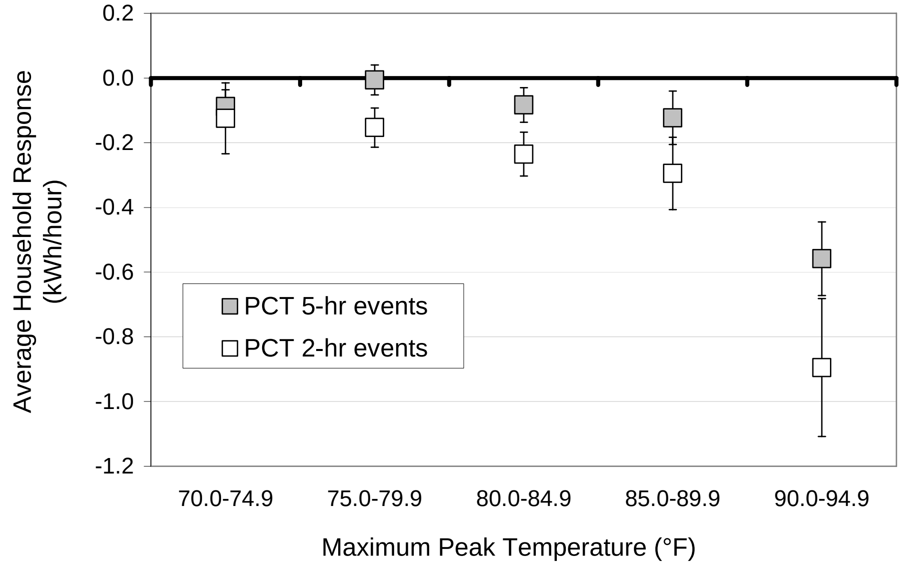

Figure 9. Mean PCT household response, by temperature and length of event

Figure 10 shows the average hourly household load for the PCT group on both normal and five-hour critical days between 90 and 94.9°F, when five-hour response was highest. Like the results for manual group shown in Figure 5, these results indicate minimal shifting of load to off-peak hours. Most surprising is the lack of rebound after the event period, when one would expect the vast majority of the air-conditioning units to begin running simultaneously, with the effect of causing a higher than normal demand.

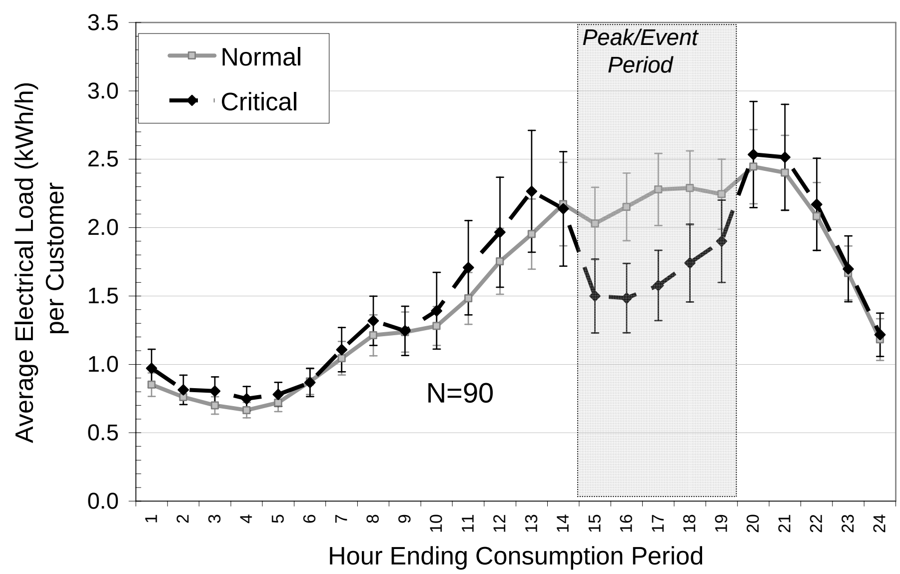

Figure 10. Hourly PCT household usage on normal and five-hour critical days, 90-94.9°F

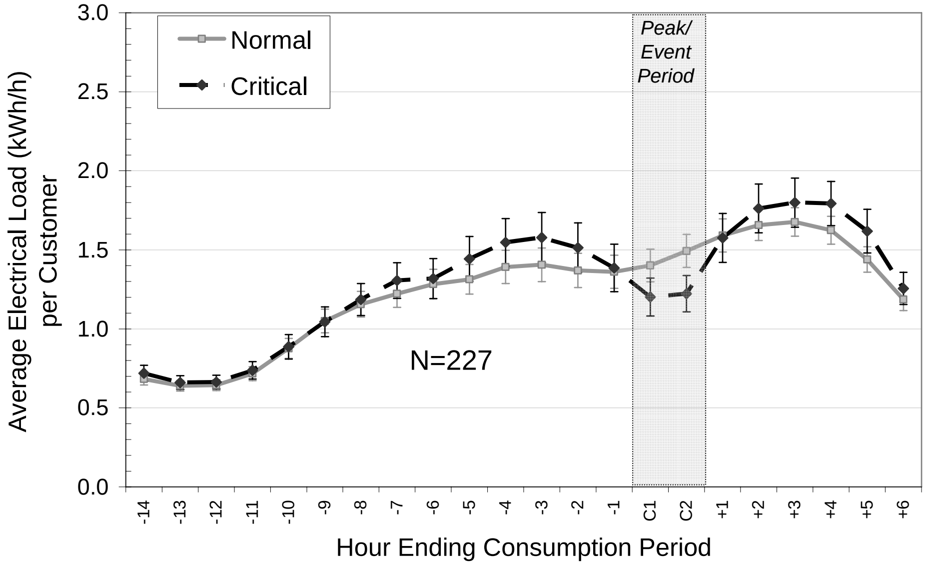

Figure 11. Hourly manual household usage on normal and two-hour critical days, 80-84.9°F

Figure 11 shows the average hourly household load for the PCT group on both normal and two-hour critical days between 80 and 84.9°F. The overall load shapes illustrated here are roughly representative of all the normal and two-hour critical load shapes between 70 and 89.9°F. In these lower temperatures, it is unclear whether the visible shift from critical hours to pre- and post-event hours is a result of behavioral changes or PCT activity. Above 90°F (not shown), negative response to two-hour critical events encompasses eight or nine hours, rather than just the two critical hours as shown in the lower temperatures. We are unable to explain this result.

Comparing Manual and PCT Group Response

Given the above results, we then considered the question of how the CPP response might differ between those with and those without automatic controls. Unfortunately, the results of the manual and PCT groups provided above cannot be compared directly because the samples consist of different customer types: the manual group is representative of the general statewide population, while the PCT group represents only high-use single-family homes with central air-conditioning in SPP climate zones 2 and 3 in San Diego. To provide some initial insights on this issue, we recalculated manual response excluding all participants except those 126 living in large single family homes in climate zones 2 and 3 with central air conditioning. Small sample sizes disallowed further restriction by utility. Average normal load shapes for the new manual and PCT groups did not differ statistically (α=0.1), but mean demand differed by about 15% across hours as shown in Figure 12.

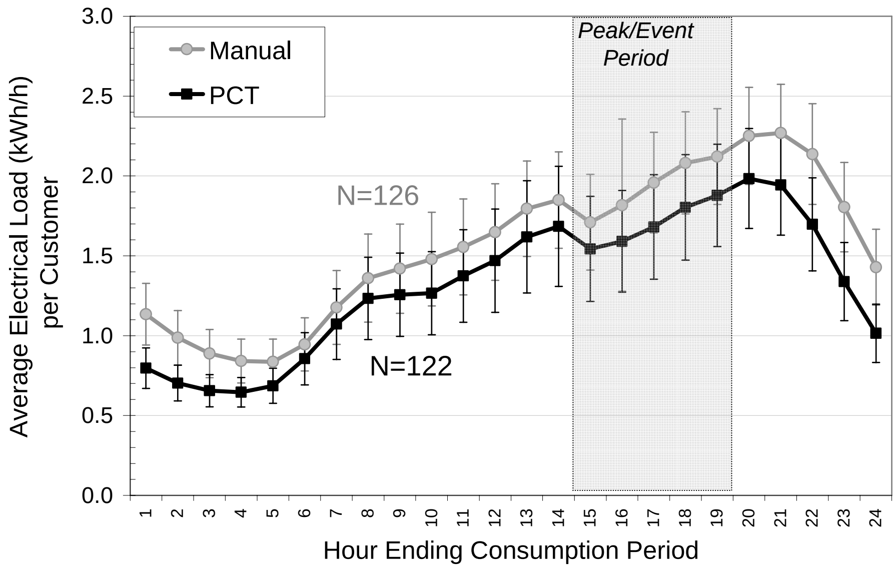

Figure 12. Average load shapes for manual and PCT groups on normal weekdays, averaged across 70-94.9°F temperature bins

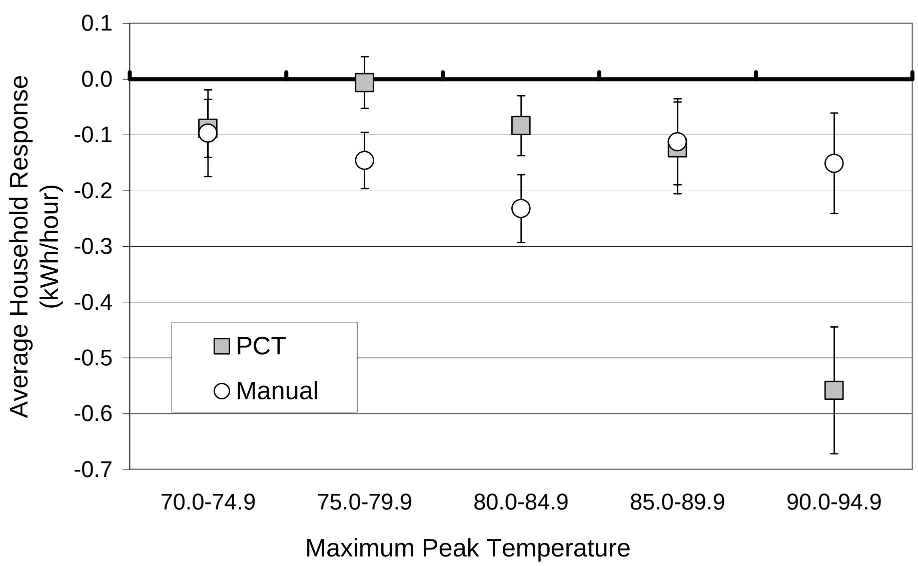

Figure 13. Comparing mean response of high-use single family homes, with and without PCTs

Our results indicate that response for the manual and PCT groups are the same in two of the five temperature bins (70-74.9°F and 85-89.9°F), manual group response is higher between 75°F and 84.9°F, and PCT group response is higher in the 90-95°F temperature range. Plotting the estimates as a fraction of load did not change these overall results. Given the aforementioned sampling inconsistencies, these mixed results, and the lack of data above 95°F, we recommend further research in this area.

Estimating System Impacts

This section provides an example of how the above results might be extrapolated to produce rough estimates of system-wide demand response. To ground our example in reality, we use data from the six electrical system emergencies called by the California Independent System Operator (ISO) from 2002 to 2005. The dates of these six emergencies are listed in the first column of Table 7. For each emergency, we then use nine representative weather stations to estimate the percentage of customers statewide that were exposed to the temperature ranges designated in this study. System loads are taken from California ISO data, while residential loads are estimated based on average residential usage for those days in the two largest California service territories.

We present results for two scenarios in Table 7. In the first, under column D, we assume that all of the approximately nine million customers in the California ISO service area are on a CPP rate without technology. The second scenario, listed under column E, differs in that we assume that high-usage customers with air conditioning, which is about one-quarter of California homes, use PCTs to respond to events. In this calculation, we conservatively estimate that these customers represent only one-quarter of California residential load. Residential response values are calculated as temperature-weighted averages of the response values given in Table 4 and Table 5. System savings are calculated as the quotient of residential response in GW and system peak load. The values given in Table 7 indicate that manual response might have offset between one and three percent of system load on these event days, while use of PCTs by large customers might have offset an additional one percent of system load. [6] With only a 2-3% load difference between stage 2 and stage 3 emergencies in California, these results imply that the load reductions gained through residential CPP rates, with or without PCTs, could be an effective resource for avoiding blackouts.

Table 7. Hypothetical effects of residential CPP rates with and without PCTs on actual California system events 2002-2005

A. Date	B. Peak Load		C. Temperature Exposure		D. All Manual Response			E. Manual and PCT Response		
	Res. (GW)	*System (GW)*	*>90°F (%)*	*>95°F (%)*	*Res. (%)*	*Res. (GW)*	*System (%)*	*Res. (%)*	*Res. (GW)*	*System (%)*
7/9/02	13.3	40.7	66	43	-8	-1.0	-3	-19	-1.4	-3
7/10/02	14.0	40.8	54	54	-9	-1.3	-3	-16	-1.5	-4
5/28/03	11.6	38.4	54	38	-7	-0.9	-2	-16	-1.1	-3
3/29/04	7.4	31.8	56	0	-4	-0.3	-1	-17	-0.5	-2
7/21/05	13.7	43.1	56	56	-9	-1.2	-3	-17	-1.5	-3
7/22/05	13.8	43.1	66	56	-9	-1.3	-3	-19	-1.6	-4

Discussion and Recommendations

The importance of maintaining system reliability has been highlighted internationally in outages that have caused major economic disruptions and safety hazards. This research has shown that dynamic pricing in the residential sector can be used to reduce peak demands, especially during the hottest days and hours of the year, when outage risks are highest. Our results show that residential response to CPP was highest when maximum daily

[6] Note that these values illustrate a statewide response to emergencies. In real-life, however, emergencies tend to be localized as a result of transmission failures or unusually high local temperatures. Rough response values can be estimated for local emergencies in the same way, using local temperature and load values.

temperatures were above 90°F. With few exceptions, however, SPP participants responded to CPP events at all temperatures. This means that CPP can provide reliability value on a year-round basis, whereas AC load control programs are only useful during the summer cooling season.

Our analysis also indicates that response to CPP events was higher when critical event periods were shorter. For the group with PCTs, average hourly response to two-hour critical events was nearly double the response to five-hour events. We expected this result to occur as a consequence of AC units gradually coming back on as indoor temperatures reached the higher setting; however, hourly analysis shows fairly steady and even increasing response across the five-hour period. Unfortunately, event duration variation was not part of the experimental design for the manual group.

Comparison between five-hour event response of those with and without PCTs provided mixed results. Above 90°F, response of customers with PCTs was nearly four times the response of a comparable group of participants without PCTs. Between 75°F and 84.9°F, this relationship is reversed, with the manual response about four times the PCT response. A possible explanation of these results is that customers with PCTs rely on the PCT to respond to price and so do not pay much attention to the CPP event signal. Thus, when temperatures are low and air-conditioning is not being used, there is no response. On the other hand, those without PCTs must consciously adjust thermostat settings to respond to CPP events in hot weather. These customers are more likely to be aware of the need for action during CPP events, and thus may be more likely to intentionally change energy-use behavior during mild weather events as well. Assuming that most system events occur when temperatures are above 90°F, use of PCTs may increase response. However, consideration of public funding or PCT standards should take into account the significant response of those without PCTs when performing cost-benefit analyses.

An additional factor in evaluating the reliability value of CPP is how it compares to peaking generation plants in terms of costs and reliability benefits. System operators are in the long-established habit of treating demand as an exogenous variable: demand is to be met regardless of the cost of power plants and fuel. In the near term, it is unlikely that CPP will be viewed by system planners as providing the same reliability benefit as peaking generation. With experience, however, system operators are likely to compile the data needed to confidently use demand response options like CPP to relieve short-lived supply shortages.

Finally, CPP rates have important equity benefits. The basic tenet of setting rates for regulated utilities is that rates should match costs. Until now the costs of metering were such that rates linking wholesale and retail prices were not feasible. Customers faced rates that had no relation to the time-varying costs of the electric system. Now, time-varying and dynamic rates like CPP are becoming increasingly possible as interval metering costs decrease. Under CPP rates, particularly those with appropriate TOU cores, customers can be charged more for electricity when it costs the utility more and less for electricity when it costs the utility less. CPP rates are also more equitable than AC cycling incentive payments, which are disbursed regardless of program use or customer contribution.

Limitations of this Study

Response to dynamic tariffs can vary considerably depending on several factors. Some of the characteristics of the pilot design and data analysis that could affect response results include the following.

- **Sampling Bias.** The voluntary nature of the SPP sampling method would cause inflated response results if volunteers were more responsive than those who rejected the offer to participate. A rigorous analysis described in an early draft of the 2003 Impact Assessment concluded that, based on 19 *measured* variables, the CPP treatment group was an unbiased sample [15]. It is plausible, however, that the 20% who accepted the participation request were simply more responsive to requests in general, an immeasurable variable, and so more likely to be more responsive to the rate as well. It is impossible to avoid this type of bias in any voluntary experiment, and also impossible to determine to what extent the potential bias exists.
- **Participation Payment.** It is not clear how the participation payment affected results, if at all. It might have discouraged response in otherwise responsive customers, who considered bill savings insignificant in comparison to the $175 cash payment. On the other hand, it might have more readily persuaded customers who were unusually attentive to monetary issues. Such customers might be more likely to respond as a result of this pre-existing, but unmeasured, characteristic.
- **Timing and duration of the critical event.** The PCT group analysis showed that the two-hour events elicited considerably more response than the five-hour events. The critical period for the manual group was always 2 p.m. to 7 p.m. A longer, shorter or more flexible critical period would likely have resulted in different response estimates. For example, in Figure 7 the event ends before residential loads reach their maximum in hour 20. Had the event been called in just hours 19 and 20, average response would likely have been larger and would have better coincided with the winter system peak.
- **Analytical temperature differences.** Our analysis relies on a comparison of usage on normal and critical days at the same temperature. Values listed in Table 2 indicate that, compared to normal days, average temperatures were slightly higher on hot CPP days and slightly lower on cold CPP days. This will have the effect of underestimating response values, since loads are higher on hotter summer days and colder winter days.

Further uncertainties arise when considering that these results show response in only the first 15 months of a new tariff. The SPP Impact Evaluation showed that response rates in the first and second summers were statistically the same [5]; however, extrapolation out to 10 or 15 years is not possible. Over time, the following factors might change the magnitude of residential response to CPP.

- **Customer Learning.** Response to a longer-term CPP rate could increase as customer understanding of the rate, their energy use, and opportunities for savings improved.
- **Technology Investments.** This and previous studies provide evidence that energy consumption information displays and automated end-use controls can increase energy savings [16, 17]. In the longer term, increasing availability of and investment in such technologies could significantly increase response.

- **Efficiency Investments.** Investments in efficiency measures in response to the new tariffs would have the effect of increasing overall savings at the expense of real-time demand response potential. For example, replacing an incandescent light bulb with a compact fluorescent light bulb decreases the demand response potential of that particular end-use by about two-thirds. We do not consider this a problem, since efficiency improvements as peak reduction measures reduce the need for demand response in the first place.

Future Research

Future research might address some of our more unusual findings. For example, we found unexpectedly low response results in the 60-64.9°F and 90-94.9°F temperature bins for the manual group. Other unexpected findings presented here include the two-hour event response for the PCT group, which was higher than expected below 90°F and extended well beyond the critical period when maximum temperatures exceeded 90°F. Finally, we consistently found a lack of load rebound at higher temperatures for all of the experimental groups, despite expectations that synchronized AC cycles would induce a larger than normal load immediately following the event.

PCTs are currently being considered for California building standards. Given our mixed results in the comparison between those with and without PCTs, it is important that any PCT cost-effectiveness analysis consider the apparent lack of response below 90°F, while above 90°F counting only the CPP response beyond what can be obtained without technology. While our analysis provides a cursory examination of this issue, it was based on data not specifically designed for this comparison. Consequently, we recommend that future research provide a more comparable dataset.

One issue alluded to but not examined in this study is: What is the optimum timing and duration of a CPP event, given specific system conditions? For example, California system loads peak twice on cold days, once at 8 p.m. just *after* the CPP events end. This implies that cold weather events for the manual group were called too early (see Figure 7). Our results also show that duration must be considered, since there is a significant tradeoff between event duration and the magnitude of response.

As stated previously, our results represent the response to CPP events after the core TOU is in place; they do not address response to the core TOU rate. One question this raises is: Based on these results, what do we know about response to a critical event when the core rate is flat rather than TOU? From economic and engineering perspectives, we expect that the real-time response of customers on a flat core rate would be higher than the real-time response of customers on a TOU core rate, because a flat rate would not encourage the daily efficiency and conservation measures a TOU rate would. For example, under a TOU rate, a customer might program her thermostat to increase the set point by two degrees to 78 during the peak period every day. During critical events, she might be willing to forgo another two degrees to 80. If instead, the core rate were flat, she would leave her thermostat at 76 every day except critical days, during which she would increase the set point to 80. While the total response to the *tariff* on event days is the same in these two cases, the response to the *CPP event* is larger in the case where the core rate is flat, because the baseline load is larger. From a behavioral perspective, on the other hand, we suspect that a CPP rate with a TOU core would affect greater overall response than would a CPP rate with a flat core because those regularly accustomed to responding to a TOU rate would likely have a better understanding of the actions needed to respond to a critical event. Further research in this area is warranted.

The limited data we have on the most extreme temperature conditions indicate that response drops off in the hottest and coldest weather. This result corroborates anecdotal information and is logical, as one might conjecture that in extreme temperatures comfort through space heating and cooling becomes more valuable than the cost of electricity needed to supply it. Future research might look for further evidence upholding or refuting this hypothesis. In addition, future research might consider to what extent this trend, if actual, is a problem, given that only a small percentage of customers are likely to be exposed to such extreme temperatures, and when they are, an even larger percentage of customers are likely to be exposed to the high-response temperature ranges.

Finally, the results presented here were derived from experimental data spanning only 15 months. As discussed previously, there are many possible outcomes for a longer term response. Customers could learn with education and practice, increasing manual response, and might invest in more efficient appliances to reduce peak demand needs. Where event signals were broadcast, customers might also invest in control technologies such as PCTs to automatically respond to event signals. On the other hand, the possibility exists that customers would become less sensitive to events with time, as the newness of the rate subsided. We suspect that such temporal apathy might be hastened by excessive or unexplained events. These issues should be considered in any future long-term implementation of CPP tariffs.

Conclusions

From a system perspective, dynamic pricing is promising as a means of linking wholesale and retail electricity markets more directly than can be done with static rates. This link is important for economically encouraging demand reductions when the system needs it most. Recent cost reductions in the metering systems needed for dynamic pricing have prompted increased interest in residential dynamic rate offerings.

This study examined the residential demand effects of CPP tariffs on two different groups. The first group, designed to be representative of the California population, was given only the most basic components of a CPP tariff: a CPP rate with a TOU core, an interval meter, and personal notification of high-price events. These customers responded to high price signals manually. In addition to the basic components, participants in the second group were given PCTs that allowed automatic control of air-conditioning units when the critical event signal was received. Since the sample for this second group consisted only of high-use customers with air-conditioning, the two groups were not directly comparable.

We calculated response as the difference between peak usage on normal days, when participants paid the TOU peak price, and peak usage on critical days, when participants were given advance notification and paid the critical peak price. For both groups, we show that the average response depends on the maximum temperature during the critical peak event, with greatest response occurring during the hottest temperatures. Manual response to five-hour CPP events averaged -13% above 95°F, -4% between 60°F and 94.9°F, and -9% between 50°F and 59.9°F. Average five-hour response of the PCT group reached -25% between 90°F and 94.9°F, while response to two-hour events reached -41% in this temperature range.

To allow rough comparison between the manual and PCT groups, we recalculated response values for high-use customers with air-conditioning in the manual group. We found that the manual group responded more between 75°F and 84.9°F, while the thermostat group responded more above 90°F. As California currently considers requiring PCTs in Title 24 building standards, these results warrant further research.

Assuming these results are representative of a statewide CPP rate, California could count on about 1 GW load reduction from residential CPP on hot event days, and about one-third of that response on mild days. Use of PCTs by one-quarter of the residential load would increase CPP event response by about 25%.

While there are many areas for potential future research, we consider the following to be of greatest import:

- improved comparison between response of those with and without PCTs
- optimum CPP timing and duration under various system scenarios
- comparison between demand effects of CPP rates with flat or TOU cores
- longer term CPP rate effects (e.g. five to ten years)

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Appendix A. Calculating Average Hourly Load Response

Response_{ij} =

$$\frac{\sum_{s=1}^{12}\left(\frac{\sum_{p=1}^{P_{ijs}}\left(\frac{\sum_{c=1}^{C_{ijsp}} Usage_{C_{ijsp}}}{C_{ijsp}}\right)}{P_{ijs}}\times\frac{Exp_s}{Size_s}\times State_s\right)}{\sum_{s=1}^{12}\frac{Exp_s}{Size_s}\times State}-\frac{\sum_{s=1}^{12}\left(\frac{\sum_{p=1}^{P_{ijs}}\left(\frac{\sum_{n=1}^{N_{ijsp}} Usage_{N_{ijsp}}}{N_{ijsp}}\right)}{P_{ijs}}\times\frac{Exp_s}{Size_s}\times State_s\right)}{\sum_{s=1}^{12}\frac{Exp_s}{Size_s}\times State} \quad (1)$$

Where: i = temperature range (from Table 2); j = hour of the day j (1-24); s = stratum; p = participant; c = critical day; n = normal day; P_{ijs} = number of participants in stratum s having both normal and critical values in temperature range i for hour j; C_{ips} = number of critical days in temp range *i* for participant *p* in stratum *s;* N_{ips} = number of normal days in temp range *i* for participant *p* in stratum *s;* Exp_{is} = number of participants in stratum *s* exposed to temperatures within range *i;* $Size_s$ = total number of participants in stratum *s;* $State_s$ = statewide population weighting for stratum s from Table 1; $Usage_{Cijsp}$ = kWh usage for participant *p* in stratum *s*, temperature bin *i*, and hour *j* on critical days; $Usage_{Njisp}$ = kWh usage for participant *p* in stratum *s*, temperature bin *i*, and hour *j* on normal days

Note that a simplified equation with the same results could be obtained by first calculating the difference between normal and critical days for each customer and then applying the averaging and weighting schemes. We chose the method outlined above to allow graphical time-series comparisons of average hourly load values for normal and critical days. We considered these comparisons central to our results.

Appendix B. Comparison to Results of the SPP Evaluation

The major differences between our study and the SPP Impact Evaluation are indicated in Table B1. Of critical importance is the fact that the analytical method we use to calculate response produces results that are *not directly comparable to SPP Impact Evaluation results*. In this study, we contrast usage of the CPP group on critical days with their usage on normal days, during which a two-price time-of-use rate is in effect. The SPP Impact Evaluation contrasted CPP group usage to that of a control group on a time-invariant rate. Because similarities and differences between these two sets of results are of interest, we provide an indirect method of comparison in the Discussion section.

Table B1. Differences between our analysis and the SPP Impact Evaluation

Study component	SPP Impact Evaluation	This paper
Data collection	No difference	No difference
Temperature binning	By climate zone	By 5-degree temperature bin
Temporal binning	By peak/off-peak rate period	By hour and by rate period
Control data	Electrical usage of a control group on a flat rate	Electrical usage of CPP participants on normal days with similar max temperature
Self-selection bias correction	Pretreatment data	Within-customer comparison negates self-selection issue
Load impact analysis	Calculated from econometric estimates of price elasticity	Calculated as population-weighted average load impacts
Results	Response to the TOU+CPP rate	Response to the CPP rate only

The regression analysis indicated summer event reductions of -0.047 kW and -0.16 kW on normal and critical days respectively, and winter event reductions of -0.011 kW and -0.035 kW on normal and critical days respectively [5]. The difference between these values implies an average -0.11 response to summer events and a -0.02 response to winter events. Although direct comparison is not possible, we create proxy summer and winter response values by average response above and below 70°F, respectively. Using the customer-event weights from Column C of Table 2, we calculate a summer response of -0.10 kW and a winter response of -0.04 kW. Thus, despite different analysis techniques, our summer response proxy is nearly identical to the summer response reported in the SPP Impact

Evaluation. On the other hand, our winter response proxy is nearly double that of the SPP Impact Evaluation. This inconsistency might warrant further analysis.

Comparison to the SPP Impact Evaluation results for PCT customers is further complicated by variations in the timing of the critical peak events, which could be either two or five hours long. The SPP Impact Evaluation did not distinguish between event lengths, reporting average impacts for all events as -0.64 kW on critical days and -0.08 kW on normal days, for an average event response of about -0.56 kW. After weighting by temperature and event length, our analysis revealed an overall response of only -0.22 kW across temperature bins, largely because nearly 90% of SPP events occurred when the maximum temperature was below 90°F (see Figure 9). This discrepancy warrants further analysis.

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